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Recovery from fast crashes: Role of mutual funds☆

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ABSTRACT

We study the role mutual funds play in the recovery from fast intraday crashes based on data from the National Stock Exchange of India for a single large stock. During normal times, trading activity and liquidity provision by mutual funds is negligible compared to other traders at around 4% of overall activity. Nevertheless, for the two intraday market-wide crashes in our sample, price recovery took place only after mutual funds moved in. Market stability may require the presence of well-capitalized standby liquidity providers for recovery from fast crashes.

1. Introduction

A liquid and stable stock market plays a critical role in the economy. It channels savings into long-term illiquid investments while at the same time providing liquidity to investors, thereby promoting economic growth (see Levine, 2005). The "Flash Crash" of May 6,

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2010 focused exchanges' and regulators' attention on the need to better understand liquidity provision in the financial markets. In this paper, we focus on a particular role financial institutions play in liquidity provision during intraday crashes and recoveries.

We show that when the demand for liquidity is unusually large leading to intraday fast crashes, mutual funds (MFs) acting as standby liquidity providers are able to step in to provide liquidity, thereby helping price recovery. By looking at micro-level data, we are able to provide high-frequency evidence of MFs acting as liquidity providers during fast intraday crashes. MFs have a natural advantage in making a market for the stocks they hold when the rewards are adequate (i.e., when price concessions are large enough). They move in only after prices have dropped sufficiently, highlighting the slow-moving feature of standby market-making capital.[2]

We use a unique database of orders and transactions data for the April to June 2006 period for one of the largest firms in the NIFTY50 and SENSEX indices traded on the National Stock Exchange (NSE) of India.[3] Based on the number of trades, the NSE was the third-largest stock exchange after NYSE and NASDAQ in the world as of April 2006.[4] The NSE is organized as a limit order book market, similar to the NYSE and NASDAQ, which has become the dominant market design.[5] Even though we use data for three months in 2006 for just one large stock from the NSE, we believe that our main conclusions likely carry over to the current U.S. stock market and several other markets around the world, given the size of the NSE market and the similarities of the market structures between the NSE and the stock markets worldwide.[6] We would like to be upfront about the limitations of our data since we conduct our analyses on one stock. Even though it is one of the largest and representative stocks on the NSE, we would like to acknowledge this limitation and potential heterogeneity that exists among stocks. However, we believe that our emphasis on liquidity provision by different types of traders especially during fast intraday crashes should not be biased by the choice of a particular stock from the benchmark stock market index.[7]

Despite the above-mentioned limitation, our data have the following advantages. First, the data have a unique identifier for each broker-trader combination, which allows us to calculate the evolution of individual traders' inventory over time. Second, the data have a legal classification (mutual fund (MF), foreign institutional investor (FII), and so on) for each trader, in addition to the unique individual trader identity. Therefore, we are able to identify the types of legal entities that are standby liquidity providers. Some legal entities are natural liquidity providers and demanders: MFs can tolerate deviations from their desired holdings if prices become attractive; FIIs have a global view on the market, and thus their behavior might be affected by the shocks originating outside the Indian market. We concentrate our analysis on MFs and FIIs as these are the two largest well-known groups of institutional investors worldwide.

We show that during normal periods (i.e., not during intraday crashes), FIIs and MFs are of minor importance both in terms of their trading activity and liquidity provision as measured by their contribution to the depth outstanding in the limit order book in the close proximity of the mid-quote (these two categories jointly are responsible for less than 10% of overall trading activity and liquidity provision). We also show that FIIs and MFs have a considerably larger holding horizon than other traders in the market. Nevertheless, the importance of FIIs and MFs for intraday price fluctuations should not be underestimated as the activity of these two categories becomes crucial in turbulent times.

There were two fast crashes and recoveries in the anonymous stock used in our analysis, alongside crashes in stock market indices such as the NIFTY50 and SENSEX, which suggests that the fast crashes and recoveries we analyze were systematic in nature.[8] The first (second) crash was characterized by a 7.9% (10.2%) drop in the mid-quote within 30 min, followed by a sharp recovery of more than 60% within the 30 min following the crash's trough.

The unusually large liquidity shocks in both crashes were due to large selling pressure coming from FIIs (as defined by the NSE). We find that MFs were patient traders, buying and selling at better prices than other traders on average. Some MFs entered the market and bought only during the crash days. Moreover, net aggressive buying by MFs Granger-caused a rise in prices during the crash days; however, there was no observed causality during non-crash days. Further, returns did not Granger-cause net aggressive buying by MFs

[2] Another potential reason for the slow-moving nature of MFs' intermediation capital could be that a sharp drop in a stock's price draws MFs' attention, after which MFs have to evaluate whether this drop is due to lack of liquidity or adverse information. And this evaluation may take time, slowing the deployment of market-making capital.

[3] The NSE became the largest stock exchange in India in terms of volume traded, overtaking the Bombay Stock Exchange (BSE) at the end of 1995.

[4] According to the World Federation of Exchanges, the largest exchange in the world based on number of transaction was the NASDAQ with more than 100,000 transactions per day, followed by the NYSE with around 91,000 transactions per day and the NSE with around 57,000 transactions per day as of April 2006.

[5] NASDAQ is a hybrid market (i.e., dealer market with a limit order book).

[6] We acknowledge that no overnight short-selling is allowed in equity markets in India as opposed to the U.S. However, given that we focus on intraday crashes and recoveries, any restrictions that apply overnight are of a minor concern in such context. In addition, overnight short-selling restriction could be overcome through single-stock futures (the single-stock futures market is quite large in India as compared to U.S.). We also note that high-frequency traders and day traders (short-term traders) tend to end their day flat, hence they are unlikely to be influenced by any overnight restrictions. We show in the Internet Appendix that the trading behavior of short-term traders during intraday crashes was similar to that of high-frequency traders during the Flash Crash of May 6, 2010 in the U.S. market.

[7] We provide an external validity check by comparing our anonymous stock to the other stocks in the NIFTY50 and to stocks in S&P 500 in Section 2.

[8] We note that intraday fast crashes are not unique to emerging markets. Such events also occur in developed markets as manifested by the Flash Crash of May 6, 2010 in the U.S. market during which both the main stock market index and its constituents experienced a fast crash and recovery as documented by, for example, Kirilenko et al. (2017) and Menkveld and Yueshen (2019), and by the 121 fast stock-specific as well as 27 market-wide intraday crashes in France over 2013 as documented by Bellia et al. (2020).

during crash and non-crash days. This is consistent with the hypothesis that buying by MFs helped price recovery; however, price recovery did not cause MFs to start buying.[9]

Our paper contributes to two streams of literature: (1) the role of financial institutions in liquidity provision and (2) causes of intraday fast crashes and recoveries.[10] From the first stream of literature, we know that (a subset of) MFs provide liquidity to the market during normal times. Keim (1999) conjectures that MFs are natural liquidity providers in the small-cap (and thus, illiquid) stocks they hold. Da et al. (2011) come to similar conclusions by showing that the Dimensional Fund Advisors Micro Cap fund added 20.5 bps per quarter to performance through liquidity provision. The degree to which institutions participate in the liquidity provision process depends on their characteristics, such as organizational structure (open-end versus closed-end funds) and holding horizon. Aragon (2007) and Agarwal et al. (2009) find that hedge funds with large redemption restrictions have larger returns, presumably because they are able to invest in illiquid assets and obtain an illiquidity premium, although the authors do not provide a direct evidence on whether funds consume or supply liquidity. Çötelioğlu et al. (2020) identify leverage, age, asset illiquidity, and reputational capital as a relevant set of characteristics that explain the exposure of hedge funds' liquidity supply to funding conditions. Giannetti and Kahraman (2018) find that closed-end mutual funds and hedge funds with large share restrictions are more inclined to trade against long-term mispricing than open-end mutual funds and hedge funds with small share restrictions. While previous studies focus on the equity markets, Anand et al. (2020) provide similar evidence for bond markets and show that there is a subset of mutual funds that specialize in liquidity provision in corporate bonds.

Some institutions are in a better position to provide liquidity during turbulent market conditions than others. Cella et al. (2013) show that 13F institutions that have long-term trading horizons tend to be liquidity providers, while short-term 13F institutions tend to demand liquidity from the market during turmoil periods (with the main focus on the period surrounding the collapse of Lehman Brothers). Anand et al. (2013) emphasize the crucial role played by MFs specializing in long-term liquidity provision in the market recovery for the 2007–2009 financial crisis. In contrast, Manconi et al. (2012) provide evidence on the subset of institutions (those with large holdings of securitized products) enhancing shock propagation from securitized product markets to corporate bond markets during the 2007–2009 financial crisis.

We note that the above-mentioned papers describing liquidity provision by institutions during financial turmoil focus on market crashes that took longer to recover from than the crashes we study. Specifically, we focus on *intraday* market crashes and recoveries, thus providing evidence that there exists a subset of institutions that specialize not on the long-term liquidity provision, but rather on the intraday liquidity supply. An intraday crash is a liquidity shock that makes a stock illiquid at a given point in time. We find that a subset of MFs that act as natural standby liquidity providers help the market to recover from the intraday fast crashes, which is consistent with earlier findings in the literature focused on long-term crashes (e.g., Anand et al., 2013).[11]

Our data allows us to track the exact timing of transactions and order submissions coming from all MFs and FIIs without relying on the inferred capital flows coming from institutional investors, thus providing insight on their role in intraday price dynamics. Most previous studies investigating the role of institutions in liquidity provision utilize quarterly data and thus have to rely on inferred capital flows. Da et al. (2011) using detailed data from Dimensional Fund Advisors note that usage of inferred flows from quarterly data leads to only 66% of transactions being correctly classified as liquidity demanding or liquidity providing (though such classification works significantly better than random assignment in the two groups). The two studies that use data on individual transactions by MFs and hedge funds provided by Abel Noser Solutions are Anand et al. (2013) and Çötelioğlu et al. (2020), respectively. However, these data cover only the subset of the population of mutual and hedge funds and are based on self-reporting by institutions. In contrast, our data cover the *whole population* of institutional investors, as well as other traders. The latter allows us to exploit trading network changes during intraday crashes and recoveries. It also allows us to trace not only transactions, but also limit order submissions; thus, we can provide evidence on another dimension of liquidity provision that previous studies fail to uncover due to the absence of necessary data.

We also contribute to the literature investigating the causes of intraday fast crashes. The focus of the recent literature on fast crashes has been on whether high-frequency traders (HFTs) were instrumental in initiating and/or accentuating the fast crashes. Easley et al. (2011) show that order-flow toxicity increased in the hours before the Flash Crash, making liquidity provision costly and eventually leading to the withdrawal from the market of many liquidity providers, most of whom were HFTs. In contrast, Kirilenko et al. (2017) show that HFTs were important market participants (jointly responsible for 34% of the trading volume in E-mini S&P 500 futures on the days surrounding the Flash Crash) and that their behavior did not change during the Flash Crash. Subsequently, Menkveld and Yueshen (2019) found that cross-market arbitrage typically conducted by HFTs broke down prior to the Flash Crash, consistent with arguments in Easley et al. (2011). In addition to the studies on the role of HFTs in crashes, Kyle and Obizhaeva (2019) document five cases wherein large bets made by institutional investors led to price crashes, three of which occurred well before the rise of high-frequency trading.

The above-mentioned papers focus on identifying why crashes occurred and on understanding the role HFTs play in this process. In our study, we find that large selling by FIIs initiated both crashes, which is consistent with the findings in previous studies. We add to

[9] Note that crash-day causality measures the average effect during the entire crash day. The market drawdown period is too short to estimate causality during that period alone.

[10] In Appendix B, we provide a summary of the findings with regard to liquidity provision in a few closely related papers.

[11] We note that out of 23 mutual funds present on the market during the two days with intraday crashes only 5 were active during the crash periods. In addition, inventory of those 5 mutual funds remained stable for the month before and after intraday crashes took place highlighting their specialization in intraday liquidity supply.

the literature by also investigating the necessary condition for recovery from such fast intraday crashes and showing that buying by MFs stabilized the market and helped it recover from the crashes, despite they having been slow to move in. Mitchell et al. (2007) make a related observation regarding the slow-moving nature of market-making capital using data from the convertible debt market,[12] and Duffie (2010) examines the implications using a theoretical framework.

When the market crashes, MFs can pick the stock that is most attractive according to some "fair value" model they use. Only MFs that are well-capitalized (i.e., holding enough cash) can act quickly and take advantage of such opportunities, consistent with the evidence provided by Simutin (2014), who documents that mutual funds with excess cash holding outperform their peers by over 2% per annum.

To summarize, we provide a comprehensive analysis of the role of slow-moving standby liquidity providers during normal times, price crashes, and recoveries. The rest of the paper is organized as follows. In Section 2, we describe the data and introduce trader classification used in the paper. In Sections 3 and 4, we provide descriptive analysis of the trading patterns of different traders during whole sample period and during intraday fast crashes and recoveries, respectively. In Section 5, we discuss the behavior of standby liquidity providers during the two crashes in our sample and describe a potential channel through which standby liquidity providers inject a stabilizing force into the market. We conclude in Section 6.

2. Data description and trader classification

We use a unique database of orders and transactions for three months in 2006 (April–June) of a large anonymous firm traded on the NSE that is part of the SENSEX and NIFTY50 indices,[13] which provides us with a unique identifier for each broker-trader combination and legal classification in the spot market.[14] Our data include detailed information on trades and quotes (the full history of the order: submission, modification, cancellation, and execution).[15] We exclude three days with half-day trading sessions from our sample (April 29, May 23, and June 25, 2006).

2.1. External validity: anonymous stock

We conduct the analysis on one single stock and clearly this is a limitation of our study. Therefore, we compare this anonymous stock to stocks that were part of NIFTY50 index to ensure representativeness for the Indian market and also to the smallest stocks that were part of S&P 500 index (bottom 20% in terms of market capitalization) to ensure that our results could be generalized to other markets as well. In particular, we collect daily data on market capitalization (in bln USD), annualized turnover, Amihud illiquidity, and market-to-book ratio as of March 2006 (before the start of our sample period) for all stocks in NIFTY50 and the smallest stocks in S&P 500 from Datastream.[16]

Panel A of Table 1 reports the quintile breakpoints, as well as the minimum, and maximum for the NIFTY50 index constituents of the monthly average of daily market capitalization (in bln USD), daily annualized turnover, daily Amihud illiquidity measure ($\times 10^8$), and daily market-to-book ratio. For the anonymous stock, we report a corresponding quintile for each of the variables. In particular, we note that anonymous stock belongs to the second market capitalization quintile (between 2.51 bln USD and 3.37 bln USD), to the fifth annualized turnover quintile (from 1.53 to 2.86), to the first Amihud illiquduity quintile (from 0.01 to 0.06) and to the third market-to-book ratio quintile (from 3.16 to 4.96). Put differently, the anonymous stock is among the most liquid (both in terms of turnover and Amihud illiquidity), but not among the largest of NIFTY50 index constituents.

In order to measure the similarity between our anonymous stock and other NIFTY50 index constituents in the four-dimensional space of the above-mentioned stocks' characteristics, for each stock i in NIFTY50, we construct a matching error with respect to stock $j \neq i$:

$$Matching\ Error_{ij} = \frac{|\frac{Mcap_j}{Mcap_i} - 1| + |\frac{Turnover_j}{Turnover_i} - 1| + |\frac{ILLIQ_j}{ILLIQ_i} - 1| + |\frac{MTBV_j}{MTBV_i} - 1|}{4}. \tag{1}$$

For each stock i, we select five stocks $j \neq i$ from the NIFTY50 with the smallest matching error and compute the average matching error across these five stocks. The distribution of the average matching errors for the IFTY50 index constituents is reported in Panel A of

[12] Mitchell et al. (2007) document that during the 2005–2006 period, convertible bond arbitrage hedge funds faced massive redemptions forcing them to liquidate their holdings of convertible bonds, leading to sharply depressed prices. Multi-strategy hedge funds supplied liquidity, although it took some time to move their capital in place. In the two fast crashes we study, liquidity shocks originated from liquidations by foreign institutional investors. Some mutual funds in our sample were able to provide liquidity; however, it took some time for them to move in – corresponding to multi-strategy hedge funds in Mitchell et al. (2007). Many other mutual funds did not provide liquidity during fast crashes and recoveries – corresponding to convertible bond mutual funds in Mitchell et al. (2007) that were not in a position to provide liquidity.

[13] See Appendix C for a detailed description of the NSE market.

[14] Kahraman and Tookes (2017) and Murphy and Thirumalai (2017) also use data provided by the NSE.

[15] See Internet Appendix Section IA.1 for summary statistics on trader and order types for spot and single futures market.

[16] Data on index constituents come from Bloomberg.

Table 1
External validity: anonymous stock. This table shows the summary statistics for the NIFTY50 index constituents, the smallest S&P 500 index constituents (bottom 20% in terms of market capitalization), and anonymous stock. Panel A (Panel B) reports quintile breakpoints, minimum, and maximum for NIFTY50 (S&P 500) of the monthly average of daily market capitalization (in bln USD), daily annualized turnover, daily Amihud illiquidity measure ($\times 10^8$), daily market-to-book ratio as of March 2006. In addition, we report quintile breakpoints, minimum, and maximum of the matching error (averaged across five most similar stocks) that was constructed for each index constituent on the basis of the four above-mentioned characteristics. For the anonymous stock, we report a corresponding quintile for each of the variables. Before computing average monthly values for each of the variables, we winsorize daily values at 2.5% and 97.5%. Daily data for market capitalization, return, trading volume, and market-to-book ratio come from Datastream. The lists of index constituents come from Bloomberg.

	Mcap	*Turnover*	*ILLIQ*	*MTBV*	*Matching error*
Panel A: Quintile breakpoints of NIFTY50					
Min	0.99	0.13	0.01	1.05	0.22
Q20	2.51	0.27	0.06	2.10	0.28
Q40	3.37	0.50	0.10	3.16	0.35
Q60	5.42	0.90	0.14	4.96	0.42
Q80	11.41	1.53	0.23	8.94	0.51
Max	24.87	2.86	0.82	20.76	1.16
# of stocks	48	48	48	48	48
Anonymous stock	Quintile 2	Quintile 5	Quintile 1	Quintile 3	Quintile 3
Panel B: Quintile breakpoints of S&P 500 (bottom 20%)					
Min	2.08	0.60	0.01	0.98	0.09
Q20	2.52	1.31	0.02	1.59	0.14
Q40	3.36	1.70	0.03	2.08	0.16
Q60	4.06	2.15	0.04	2.85	0.18
Q80	4.69	2.99	0.05	3.94	0.22
Max	5.21	7.20	0.08	15.51	0.30
# of stocks	93	93	93	93	93
Anonymous stock	Quintile 2	Quintile 4	Quintile 4	Quintile 5	Quintile 3

Table 1. We note that our anonymous stock belongs to the third quintile of the matching error distribution, suggesting that in the space spanned by the four above-mentioned stocks' characteristics, our anonymous stock is not an outlier and is thus representative of the Indian market.[17]

Panel B of Table 1 reports similar analysis for the smallest stocks in the S&P 500 (bottom 20% in terms of market capitalization). We show that our anonymous stock belongs to the second quintile in terms of market capitalization, the fourth quintile in terms of turnover and Amihud illiquduity, and to the fifth quintile in terms of the market-to-book ratio. We also construct matching error for each of the smallest stocks in the S&P 500 and our anonymous stock and select five stocks from the S&P 500 universe with the smallest matching error. We document that the anonymous stock belongs to the third quintile of the matching error distribution. In conclusion, our anonymous stock can be considered as a representative stock in the four-dimensional space of the above-mentioned characteristics for the bottom 20% of the S&P 500 and thus, the results of this study could be extended also to other markets.

2.2. Trader classification

The NSE classifies all traders in terms of their legal affiliations. There are three primary categories: individuals, corporations, and financial institutions; and 13 subcategories: individual traders, partnership firms, Hindu undivided families, public and private companies or corporate bodies, trust or society, mutual funds, domestic financial institutions, banks, insurances, statutory bodies, nonresident Indians, foreign institutional investors, and overseas corporate bodies. For the purpose of our analysis, investigating the role of institutions in the recoveries from the fast crashes, we divide traders into three categories based on their legal classification (see Fig. 1): foreign institutional investors (FIIs), mutual funds (MFs), and other traders (Other). In addition, a trader to be classified as FII or MF has to trade at least 750 shares (the size of a single-stock futures contract) on a median day when the trader is active. Traders that trade less than 750 shares per day do not have an opportunity to use the futures market for hedging purposes.[18] Each trader belongs only to one category during our sample period (i.e., traders do not switch categories from one day to another).[19]

[17] The NIFTY50 covers around 60%–70% of the total market capitalization. Our results might not hold for small and extremely illiquid stocks. However, regulators are mainly concerned with fast intraday crashes and recoveries in the main stock market indices like the S&P 500 in the U.S., which accounts for 70%–80% of the total market capitalization.

[18] Several MFs and FIIs (based on legal classification only) do not satisfy this requirement. However, their activity during the period considered is negligible. These traders are active on average during five days only and transact on average 109 shares per day.

[19] See Internet Appendix Section IA.2 for a fine-tuned classification where we expand the Other traders category.

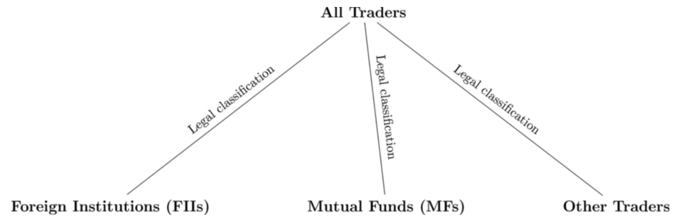


Fig. 1. Trader classification. This figure shows the trader classification scheme we use.

Table 2
Trading volume per trader category. This table shows the number of traders in each trader group, number of shares bought and sold by each trader group and proportion of trading volume attributable to each trader group. In addition, we report the trading volume and end-of-day inventory position averaged by trader-day within each trader group. We include both transaction of the regular book orders and stop loss orders. We classify traders into three categories: foreign institutions (FII), mutual funds (MF), and other traders (Other). Data on trader IDs, orders, and trades for anonymous stock for the period from April to June 2006 are provided by the NSE.

	# of traders	Total buying volume		Total selling volume		Total volume (buying + selling)		Average by trader-day	
		# of shares	% of shares	# of shares	% of shares	# of shares	% of shares	Inventory	Trading volume
FII	127	7,019,742	6.36%	8,825,689	7.99%	9,967,471.00	4.64%	99.3%	51,150
MF	268	2,947,729	2.67%	5,183,524	4.69%	8,131,253.00	3.78%	96.7%	12,187
Other	99,001	100,476,999	90.98%	96,435,257	87.32%	196,912,256.00	91.58%	30.5%	669

3. Summary statistics

In this section, we provide summary statistics of the trading activity of FIIs and MFs (see Section 3.1) and liquidity provision of FIIs and MFs as measured by their contribution to the depth of the limit order book (see Section 3.2) during our sample period.

3.1. Trading activity

We start by documenting the trading activity of the different trader categories. Table 2 shows that during our sample period there are 127 (0.1% of the total number of traders) FIIs and 268 (0.3% of the total number of traders) MFs present in the market. FIIs as a group are responsible for 4.64% of the total (buying + selling) trading volume, while MFs as a group are responsible for 3.78% of the total (buying + selling) trading volume. The trading activity of both FIIs and MFs is not concentrated on one side of the market but rather is split between the buy and sell sides.

On average across trader-days, we show that FIIs and MFs tend to have larger trading volume than other traders. In particular, the average daily trading volume of individual FII (MF) is 51,150 (12,187) shares as compared to 669 shares of individual traders from the Other category. The end-of-day inventory position $\left(\frac{\textit{of shares bought} - \textit{of shares sold}}{\textit{of shares bought} + \textit{of shares sold}}\right)$ of FIIs (MFs) is 99.3% (96.7%), while the end-of-day inventory of other traders is only 30.5%. This suggests that individual FIIs (MFs) build up their positions on a particular day (either buying or selling during the same day), while individual Other traders tend to engage in intraday trading strategies (both buying and selling during the same day).

3.2. Contribution to the limit order book depth

We next examine liquidity provision by FIIs and MFs as measured by their contribution to the limit order book depth. In particular, we look at the proportion of the total depth supplied by FIIs and MFs at the close proximity (in bps) to the mid-quote.

Table 3 reports an average of 1-min median depth in thousands of shares 10, 25, 50, 75, and 100 bps away from the mid-quote, together with the proportion of shares coming from FIIs and MFs. Both FIIs and MFs supply liquidity on both sides of the limit order book. At the bid side of the limit order book, FIIs (MFs) supply between 3.41% and 4.46% (between 1.61% and 2.42%) of the total depth outstanding. At the ask side of the limit order book, FIIs (MFs) supply between 4.84% and 6.00% (between 3.00% and 4.10%) of the total depth outstanding. The proportion of the depth supplied by FIIs (MFs) remains relatively constant while moving further away from the mid-quote (from 10 bps to 100 bps).

To sum up, we document that FIIs and MFs are different from Other traders as they have a longer holding horizon for a stock. We also show that FIIs and MFs jointly are responsible for less than 10% of the total trading volume and less than 10% of the liquidity provision as measured by their contribution to the depth of the limit order book during our sample period.[20] Despite that, the role of FIIs (MFs) is crucial during the fast crashes (recoveries).

[20] See Internet Appendix Section IA.3 for the summary statistics on the alternative measures of liquidity provision during our sample period.

Table 3
Contribution to the limit order book depth. This table shows the average contribution to the limit order book by foreign institutions (FII) and mutual funds (MF) in the proximity of the midpoint. Average depth is reported in thousands shares. Data on trader IDs, orders, and trades for anonymous stock for the period from April to June 2006 are provided by the NSE.

# of bps from the midpoint	Bid side			Ask side		
	Average depth	FII	MF	Average depth	FII	MF
10	1.92	4.46%	1.61%	1.82	4.86%	3.00%
25	5.08	4.41%	1.90%	5.03	6.00%	3.75%
50	9.89	3.91%	2.42%	10.55	5.97%	4.00%
75	14.15	3.58%	2.39%	16.52	5.24%	4.10%
100	17.90	3.41%	2.40%	16.52	4.84%	3.86%

4. Fast crashes

In this section, we identify stock price crashes and describe the behavior of FIIs and MFs during crashes. We identify crashes using two methods, both of which identify essentially the same crashes. First, we use the drift-burst statistics developed by Christensen et al. (2018) and also used by Bellia et al. (2020):

$$
\begin{aligned}
T_t &= \sqrt{\frac{h_\mu}{K_2}}\,\frac{\mu_t}{\sigma_t} \\
\mu_t &= \frac{1}{h_\mu}\sum_{i=1}^{n}\left(K\left(\frac{t_{i-1}-t}{h_\mu}\right)r_{t_{i-1}}\right) \\
\sigma_t &= \sqrt{\frac{1}{h_\sigma}\sum_{i=1}^{n}\left(K\left(\frac{t_{i-1}-t}{h_\sigma}\right)r^2_{t_{i-1}}\right)} \\
K(x) &= \exp(-|x|)1(x \le 0) \\
K_2 &= \int_R K^2(x)dx.
\end{aligned}
\tag{2}
$$

Intuitively, the drift-burst statistic compares the average 1-min mid-quote returns, r_t, computed over the rolling window before time t (with the length of the window determined by the bandwidth, h_μ) to the volatility of the returns computed over the rolling window before time t (with the length of the window determined by the bandwidth, h_σ), with the most recent observations receiving the highest weight. A crash trough is the time t when the average returns become too large with respect to their volatility. Under the null of no drift burst, T_t follows a standard normal distribution; however, when there is a drift burst, $|T_t|$ goes to infinity. We estimate drift-burst statistics for the mean bandwidth (h_μ) of 15 min and the volatility bandwidth (h_σ) of 45 min. This implies that we are interested in the crashes that develop, on average, within 15 min, similar to the Flash Crash of May 6, 2010. At the end of each 1-min interval, we compute the drift-burst statistics based on the 1-s mid-quote returns. Given that we are interested in the crashes, we focus our attention on negative drift-burst statistics. We mark 1-min intervals when the absolute value of the drift-burst statistics exceeds its critical value at the 95% confidence level as crash troughs. The critical value we employ accounts for the multiple tests, as in Christensen et al. (2018).[21] In our sample, we detect eight such troughs. The drift-burst statistic by itself does not tell us whether the crash is reverted. Therefore, we look at the cumulative returns 30 min before and after the trough. We select only those crashes that recover by at least 50%. After applying the recovery condition, only two crashes remain: those that took place on May 19, 2006 and May 22, 2006. On May 19, 2006, the trough of the crash is at 10:38 a.m. On May 22, 2006, the trough of the crash is at 11:52 a.m.

Second, we use the more intuitive crash identification rule: a 3% drop in 1-min mid-quotes over 15 min, followed by a recovery in 1-min mid-quotes of 3% over 15 min. We obtain the same two crashes with the trough point of May 19 being exactly the same as identified by the drift-burst statistic, and the trough point for May 22 being 2 min later than the one identified by the drift-burst statistic. Since the two crashes' troughs that the two methods identified are essentially the same, we use the troughs identified by the first method (the drift-burst statistic) for the analysis that follows.

For further analysis, we focus our attention on the four days surrounding the crash days from May 16 through May 25.[22] We compare the behavior of FIIs and MFs during the crash days with their behavior during the two days before and two days after the crash instead of comparing with all other days in the sample.

[21] We thank the authors for sharing the code for the estimation procedure, as well as the dataset containing the critical values of the drift-burst statistic that account for multiple testing problems.

[22] May 18 and May 23 are either missing from our data or only include trades for the first 30 min of the trading day.

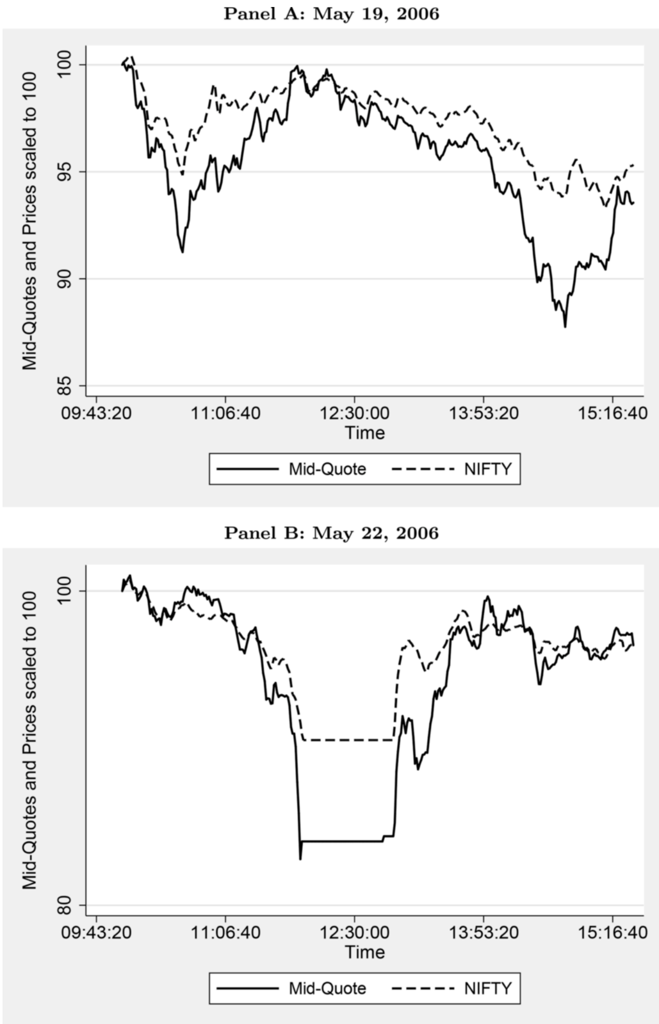


Fig. 2. Crashes. This figure shows the dynamics of the mid-quote together with NIFTY50 prices at a 1-min frequency for the two crash days: May 19 and May 22, 2006. Mid-quotes and prices are scaled to 100 at the beginning of the trading day. Data are provided by the NSE.

Fig. 2 shows the mid-quote evolutions during the trading day, together with the NIFTY50 price (median over a 1-min interval) for the two days on which the crashes happened. On May 19, we observe two events that look like a crash followed by a fast recovery. Indeed, on May 19, we identify two troughs based on the drift-burst statistic. However, only during the first event did the crashes develop and revert quickly enough. During the 30 min before the first crash's trough, prices fell by 7.9% and recovered by 5.1% (reversal of 64.5%) in the 30 min that followed. However, during the 30 min before the second crash's trough, prices fell by 6.1% and recovered in the next 30 min by only 0.6% (9.1% reversal). Put differently, during the second event on May 19, prices did not fall and recover fast enough to be classified as a fast crash. On May 22, during the 30 min before the trough, prices fell by 10.2% and recovered in the next 30 min by 7.0% (a 68.4% reversal). This crash was also characterized by a trading halt (from 11:56 a.m. to 12:56 p.m.) before market recovery took place. The two crashes were accompanied by similar movement in the NIFTY50 index, although it was less pronounced. Therefore, despite the fact that we focus on one anonymous stock, the two crashes are not idiosyncratic, but rather systematic in nature similar to the Flash Crash of May 6, 2010 in the U.S.

Fig. 3 provides graphical representation of MFs' and FIIs' trading behavior. The figure shows that selling by FIIs coincides with the crashes, while buying by MFs is followed by the market recovery. The inventory position of Other traders remains rather flat during the crash period and decreases during recovery periods, therefore the trading activity of Other traders is unlikely to play a stabilizing and/or destabilizing role in the market. Fig. 3 provides suggestive evidence that the crashes were driven by selling pressure from FIIs, while recoveries are due to buying pressure from MFs. Out of 23 mutual funds present on the market during the two days with intraday crashes, only five were active during the crash periods, yet these active MFs were able to inject enough liquidity to stabilize the market.

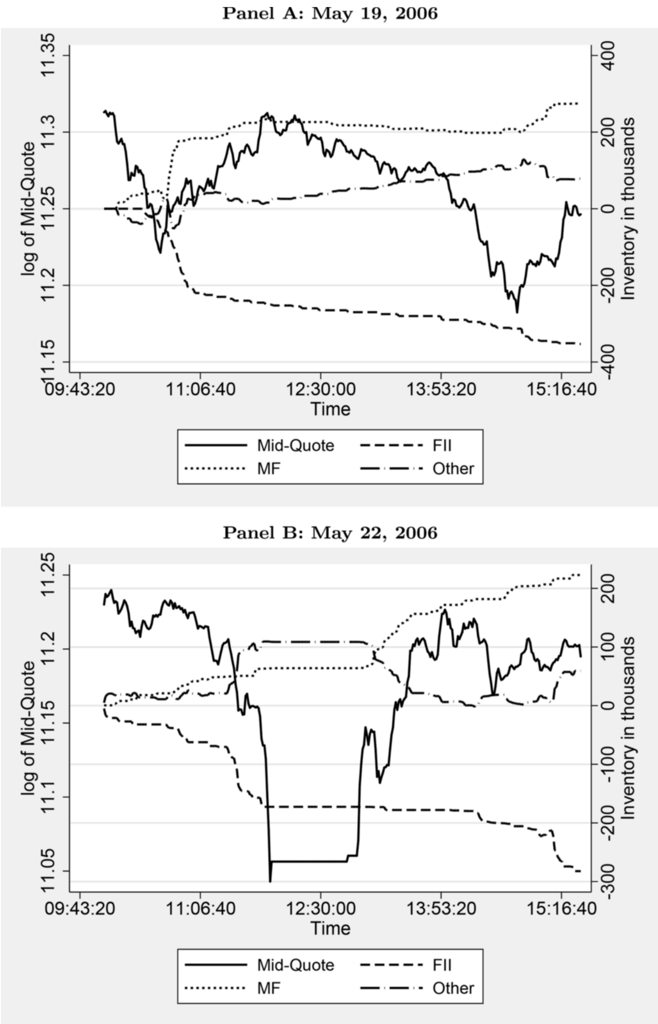


Fig. 3. Inventory dynamics during the fast crashes and recoveries. This figure shows dynamics of the mid-quote and inventory of FIIs, MFs, and other traders (Other) at a 1-min frequency during the two crash days: May 19 and May 22, 2006. Data are provided by the NSE.

These graphs demonstrate the stabilizing role of slow-moving capital (see Duffie, 2010).[23]

In addition, we examine the contribution of the FIIs and MFs to the depth outstanding in the limit order book 10, 25, 50, 75, and 100 bps away from the mid-quote during the crash and recovery periods. Tables 4 and 5 show that FIIs supply liquidity on the ask side of the limit order book, while MFs supply liquidity on the bid side of the limit order book during crash and recovery periods. These findings are in contrast to the whole sample summary statistics reported in Table 3 where the presence of FIIs and MFs is symmetric on both sides of the limit order book. Moreover, the presence of FIIs (MFs) on the ask (bid) side of the book reaches more than 20% in some cases, while for the whole sample period, the joint contribution of FIIs and MFs to the depth on the each side of the limit order book does not go above 10%. We also show that the presence of FIIs and MFs is persistent throughout the crash and recovery period on the ask and bid side of the limit order book, respectively.[24]

Overall, our results show that although during normal periods the trading activity and liquidity provision of the FIIs and MFs is relatively small, during fast crashes and recoveries their activity becomes much more prevalent.

[23] See Internet Appendix Section IA.4 for an inventory sensitivity analysis in the spirit of Kirilenko et al. (2017).

[24] See Internet Appendix Section IA.5 for the summary statistics on the alternative measures of liquidity provision during crash periods.

Table 4

Contribution to limit order book depth: Crashes. This table shows the average contribution to the limit order book by foreign institutions (FII) and mutual funds (MF) in the proximity of the midpoint for the periods from 30 to 20 min before the trough of the crash (Panel A), from 20 to 10 min before the trough of the crash (Panel B), and from 10 min before the trough of the crash to the trough of the crash (Panel C). Average depth is reported in thousands shares. Data on trader IDs, orders, and trades for anonymous stock for the period from April to June 2006 are provided by the NSE.

# of bps from the midpoint	Bid side			Ask side		
	Average depth	FII	MF	Average depth	FII	MF
Panel A: [-30–20]						
10	0.30	0.00%	0.00%	0.40	0.00%	0.00%
25	2.11	0.00%	7.39%	1.49	0.00%	0.00%
50	4.80	0.00%	18.31%	4.13	8.58%	0.00%
75	6.87	0.00%	20.29%	5.41	9.08%	0.00%
100	8.15	0.00%	18.89%	6.67	10.42%	0.00%
Panel B: [-20–10]						
10	0.22	0.00%	0.25%	0.41	0.00%	0.00%
25	1.08	0.00%	4.30%	1.79	0.00%	1.68%
50	2.23	0.00%	4.06%	4.14	3.09%	10.57%
75	3.72	0.00%	2.50%	5.58	2.20%	12.19%
100	5.65	0.00%	1.89%	6.42	2.11%	11.15%
Panel C: [-10 0]						
10	0.58	0.00%	9.30%	0.39	2.52%	0.00%
25	1.53	0.00%	6.69%	1.37	11.82%	0.00%
50	3.54	0.00%	8.41%	3.16	15.68%	0.00%
75	4.97	0.00%	6.69%	4.70	18.03%	0.00%
100	6.03	0.00%	5.98%	5.70	19.16%	0.00%

Table 5

Contribution to limit order book depth: Recoveries. This table shows the average contribution to the limit order book by foreign institutions (FII) and mutual funds (MF) in the proximity of the midpoint for the periods from the trough of the crash to 10 min after the trough of the crash (Panel A), from 10 to 20 min after the trough of the crash (Panel B), and from 20 to 30 min after the trough of the crash (Panel C). Average depth is reported in thousands shares. Data on trader IDs, orders, and trades for anonymous stock for the period from April to June 2006 are provided by the NSE.

# of bps from the midpoint	Bid side			Ask side		
	Average depth	FII	MF	Average depth	FII	MF
Panel A: [0 + 10]						
10	0.89	0.00%	9.04%	0.35	0.00%	0.00%
25	3.82	0.00%	14.94%	1.51	6.32%	0.00%
50	8.52	0.00%	20.40%	2.58	4.85%	0.00%
75	10.08	0.00%	17.93%	3.66	3.89%	0.00%
100	11.08	0.00%	16.99%	4.47	3.56%	0.00%
Panel B: [+10 + 20]						
10	0.48	0.00%	0.00%	0.51	9.52%	0.00%
25	1.40	0.00%	9.54%	2.49	8.48%	0.00%
50	2.80	0.00%	15.20%	4.25	10.87%	0.00%
75	4.85	0.00%	18.27%	5.60	16.06%	0.00%
100	6.02	0.00%	17.74%	7.86	22.13%	0.00%
Panel C: [+20 + 30]						
10	2.64	0.00%	2.57%	0.16	0.00%	0.00%
25	6.12	0.00%	0.80%	0.96	0.00%	0.00%
50	14.81	0.00%	4.16%	3.41	13.10%	0.00%
75	18.43	0.00%	4.43%	5.11	14.67%	0.00%
100	19.79	0.00%	6.53%	6.19	13.64%	0.00%

5. Role of FIIs and MFs during fast crashes and recoveries

In this section, we analyze Granger-causality between the activity of FIIs and MFs and the mid-quote returns (see Section 5.1) and discuss a potential channel that allows MFs to stabilize the market during the fast crashes (see Section 5.2).[25]

5.1. Granger-causality

So far, we have provided suggestive evidence for the cause of crashes – selling by FIIs – as well as for the cause of recoveries – buying by MFs. In this section, we investigate whether FIIs (MFs) Granger-cause crashes (recoveries) versus whether crashes (recoveries) Granger-cause FIIs (MFs) activity.

First, we compute marketable order imbalance (*MOIB*) for each trader category i as buy volume initiated by trader category i minus sell volume initiated by this trader category i, and scale it with overall (buyer- plus seller-initiated) volume in the market during a 1-min time interval t (see equation (3)). In order to determine which order initiates the transaction, we match trades with respective quotes and compare the timestamps of the two sides of the transaction. The order with the latest timestamp is the one that initiates the transaction.[26]

$$MOIB_{i,t} = \frac{Buyer\ initiated\ volume_{i,t} - Seller\ inititated\ volume_{i,t}}{Buyer\ initiated\ volume_{t} + Seller\ inititated\ volume_{t}}. \tag{3}$$

Second, we compute the limit order book imbalance (*LOIB*) for each trader category i as the median depth outstanding at the bid side of the limit order book within 100 bps from the mid-quote for trader category i minus the median depth outstanding at the ask side of the limit order book within 100 bps from the mid-quote for trader category i and scale it with overall (bid plus ask side of the limit order book) median depth outstanding within 100 bps from the mid-quote during the 1-min time interval t (see equation (4)).

$$LOIB_{i,t} = \frac{Bid\ Depth_{i,t} - Ask\ Depth_{i,t}}{Bid\ Depth_{t} + Ask\ Depth_{t}}. \tag{4}$$

Afterwards, we estimate the vector-autoregression model on 1-min mid-quote returns, marketable order imbalance (*MOIB*), and limit order book imbalance (*LOIB*) from different trader categories. We use BIC criterion to decide on the number of lags, n.

$$\begin{aligned}
Ret_t &= \alpha + \sum_{lag=1}^{n} \beta_{lag} Ret_{t-lag} + \sum_{lag=1}^{n} \sum_{i} \delta_{i,lag} MOIB_{i,t-lag} + \sum_{lag=1}^{n} \sum_{i} \gamma_{i,lag} LOIB_{i,t-lag} + \varepsilon_t \\
MOIB_{i,t} &= \alpha + \sum_{lag=1}^{n} \beta_{lag} Ret_{t-lag} + \sum_{lag=1}^{n} \sum_{i} \delta_{i,lag} MOIB_{i,t-lag} + \sum_{lag=1}^{n} \sum_{i} \gamma_{i,lag} LOIB_{i,t-lag} + \varepsilon_t \\
LOIB_{i,t} &= \alpha + \sum_{lag=1}^{n} \beta_{lag} Ret_{t-lag} + \sum_{lag=1}^{n} \sum_{i} \delta_{i,lag} MOIB_{i,t-lag} + \sum_{lag=1}^{n} \sum_{i} \gamma_{i,lag} LOIB_{i,t-lag} + \varepsilon_t.
\end{aligned} \tag{5}$$

Table 6

Granger-causality. This table shows the results of the Granger-causality tests for a vector-autoregression for 1-min returns, marketable, and limit order imbalances from different trader categories (see equation (5)). We estimate vector-autoregressions for the crash days and for the four non-crash days. We classify traders into three categories: foreign institutions (FIIs), mutual funds (MFs), and other traders (Other). For brevity, we report only those Granger-causality tests that are relevant for our analysis. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Data on trader IDs, orders, and trades for anonymous stock for the period from April to June 2006 are provided by the NSE.

Equation	19-22 of May		16-25 of May, excl crash days		
	Excluded	*p*-value	Equation	Excluded	*p*-value
Return	$MOIB_{FII}$	2.70%**	*Return*	$MOIB_{FII}$	12.00%
Return	$MOIB_{MF}$	0.00%***	*Return*	$MOIB_{MF}$	95.40%
Return	$LOIB_{FII}$	1.40%**	*Return*	$LOIB_{FII}$	0.20%***
Return	$LOIB_{MF}$	3.70%**	*Return*	$LOIB_{MF}$	54.90%
$MOIB_{FII}$	*Return*	94.00%	$MOIB_{FII}$	*Return*	33.20%
$MOIB_{MF}$	*Return*	25.50%	$MOIB_{MF}$	*Return*	42.00%
$LOIB_{FII}$	*Return*	49.00%	$LOIB_{FII}$	*Return*	8.20%*
$LOIB_{MF}$	*Return*	84.20%	$LOIB_{MF}$	*Return*	24.60%

[25] See Internet Appendix Section IA.6 for the role of short-term traders (a subset of Other traders category from the extended classification scheme, see Internet Appendix Section IA.2) in causing intraday fast crashes and recoveries.

[26] In case orders on the two sides of the transaction have the same timestamp, we cannot determine which order initiates the trade. However, there are very few such unclassified cases (0.76% of trading volume).

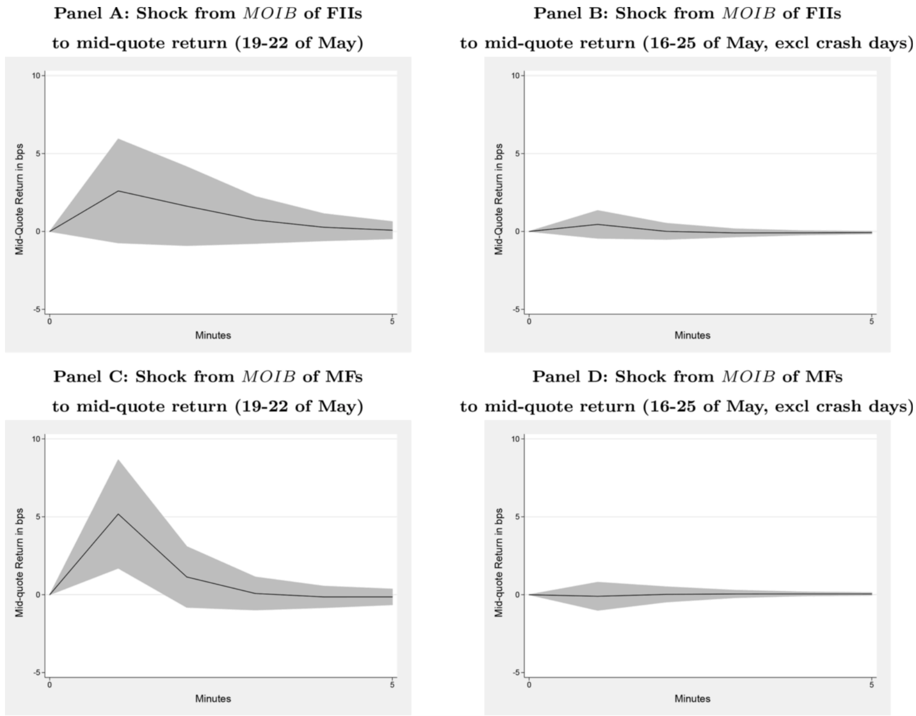


Fig. 4. Orthogonalized impulse response functions for mid-quote return from *MOIB*. This figure shows orthogonalized impulse response functions for mid-quote return from marketable order imbalance (*MOIB*) based on vector-autoregression for 1-min returns, marketable, and limit order imbalances from different trader categories (see equation (5)). We estimate vector-autoregression for the crash days and for the four non-crash days. We classify traders into three categories: foreign institutions (FIIs), mutual funds (MFs), and other traders (Other). Data are provided by the NSE.

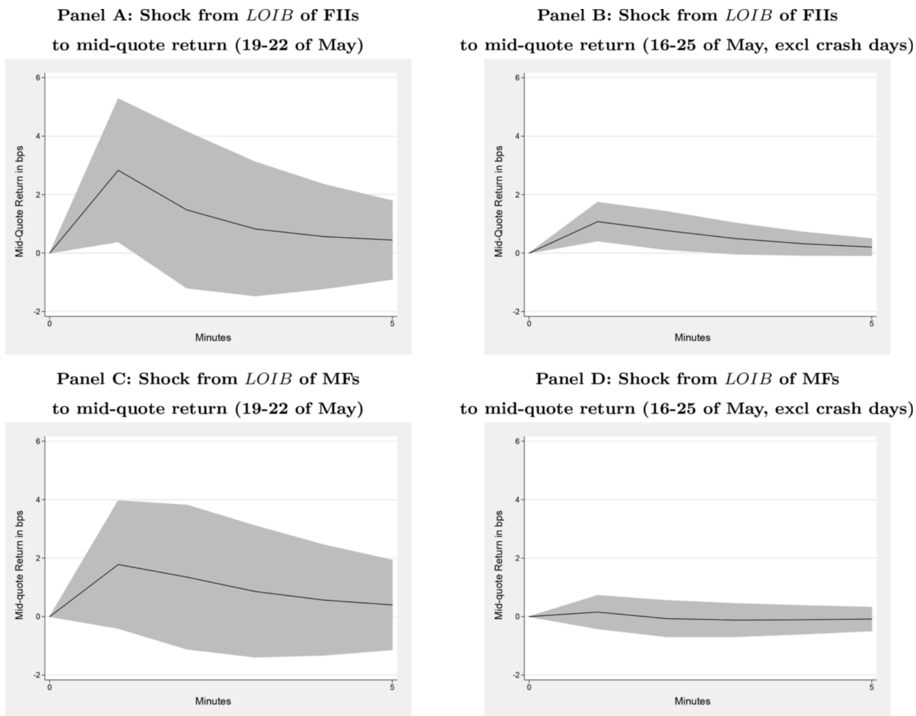


Fig. 5. Orthogonalized impulse response functions for mid-quote return from *LOIB*. This figure shows orthogonalized impulse response functions for mid-quote return from limit order book imbalance (*LOIB*) based on vector-autoregression for 1-min returns, marketable, and limit order imbalances from different trader categories (see equation (5)). We estimate vector-autoregression for the crash days and for the four non-crash days. We classify traders into three categories: foreign institutions (FIIs), mutual funds (MFs), and other traders (Other). Data are provided by the NSE.

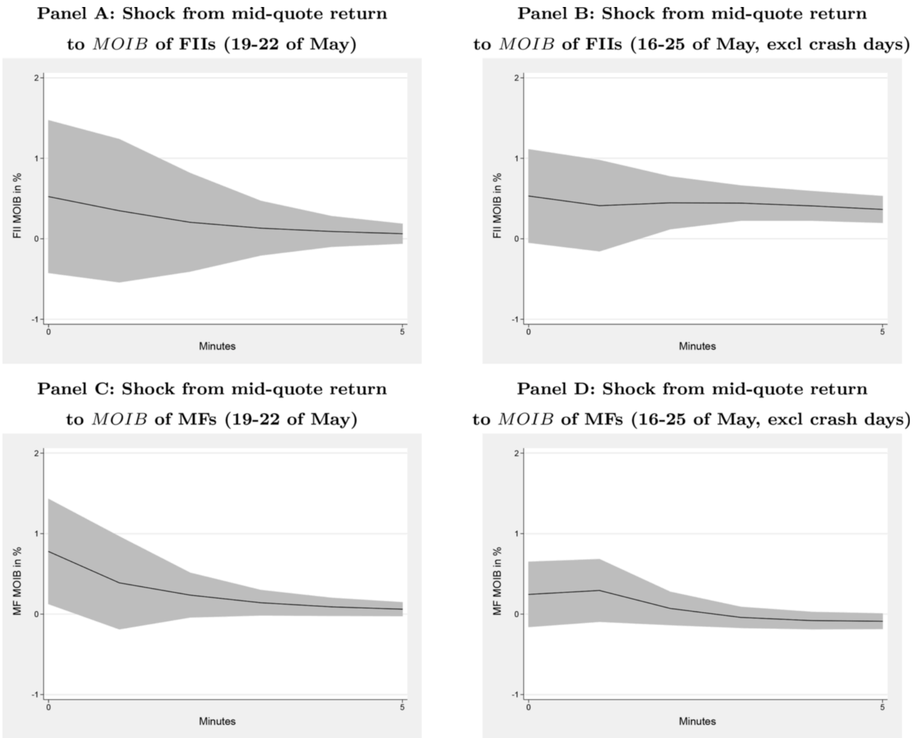


Fig. 6. Orthogonalized impulse response functions for *MOIB* from mid-quote returns. This figure shows orthogonalized impulse response functions for marketable order imbalance (*MOIB*) from mid-quote return based on vector-autoregression for 1-min returns, marketable, and limit order imbalances from different trader categories (see equation (5)). We estimate vector-autoregressions for the crash days and for the four non-crash days. We classify traders into three categories: foreign institutions (FIIs), mutual funds (MF), and other traders (Other). For brevity, we report only those impulse response functions that are relevant for our analysis. Data are provided by the NSE.

Table 6 presents the results of Granger-causality tests (for brevity, we report only results that are relevant for our analysis). We show that both marketable order imbalance (*MOIB*) and limit order book imbalance (*LOIB*) from FIIs and MFs Granger-cause mid-quote returns on the crash days. In particular, the *p*-values of the Granger-causality test from *MOIB* to mid-quote returns are 2.70% and 0.00% and *p*-values of the Granger-causality test from *LOIB* to mid-quote returns are 1.40% and 3.70% for FIIs and MFs, respectively. At the same time, mid-quote returns do not Granger-cause marketable order imbalance (*MOIB*) with the *p*-values of 94.00% and 25.50% and limit order book imbalance (*LOIB*) with the *p*-values of 49.00% and 84.20% of FIIs and MFs, respectively. On the contrary, during non-crash days, the marketable order imbalance (*MOIB*) of MFs and FIIs and limit order book imbalance (*LOIB*) of MFs do not Granger-cause mid-quote returns, nor vice versa. This is consistent with FIIs causing a crash and MFs causing the recovery.

In Figs. 4 and 5, we plot orthogonalized impulse response functions from marketable order imbalance (*MOIB*) and limit order book imbalance (*LOIB*) to mid-quote returns for both crash and non-crash days. The decomposition order is as follows: mid-quote returns, marketable order imbalance from FIIs, MFs, and Other traders, and limit order book imbalance from FIIs, MFs, and Other traders. A one standard deviation shock to FIIs' *MOIB* or MFs' *MOIB* results in a larger effect on the mid-quote returns on the crash days (around 2–5 bps at a 1-min horizon) than on the non-crash days (around 0 bps at a 1-min horizon). A one standard deviation shock to FIIs' *LOIB* or MFs' *LOIB* also results in a larger effect on the mid-quote returns on the crash days (around 2–3 bps at a 1-min horizon) than on the non-crash days (around 0–1 bps at a 1-min horizon).

In Figs. 6 and 7, we plot orthogonalized impulse response functions from mid-quote returns to marketable order imbalance (*MOIB*) and limit order book imbalance (*LOIB*), respectively. The decomposition order is as follows: mid-quote returns, marketable order imbalance from FIIs, MFs, and Other traders, and limit order book imbalance from FIIs, MFs, and Other traders. In all cases, the effect is marginal for both crash and non-crash days.

We find that MFs induce the recovery process in the spot market; however, it takes a while for them to step in. They act as standby liquidity providers that are slow in deploying their market-making capital. Our statistical tests confirm that buying by MFs leads to recovery, but recovery does not lead MFs to buy. Our findings are consistent with Keim (1999), who expresses the view that MFs are

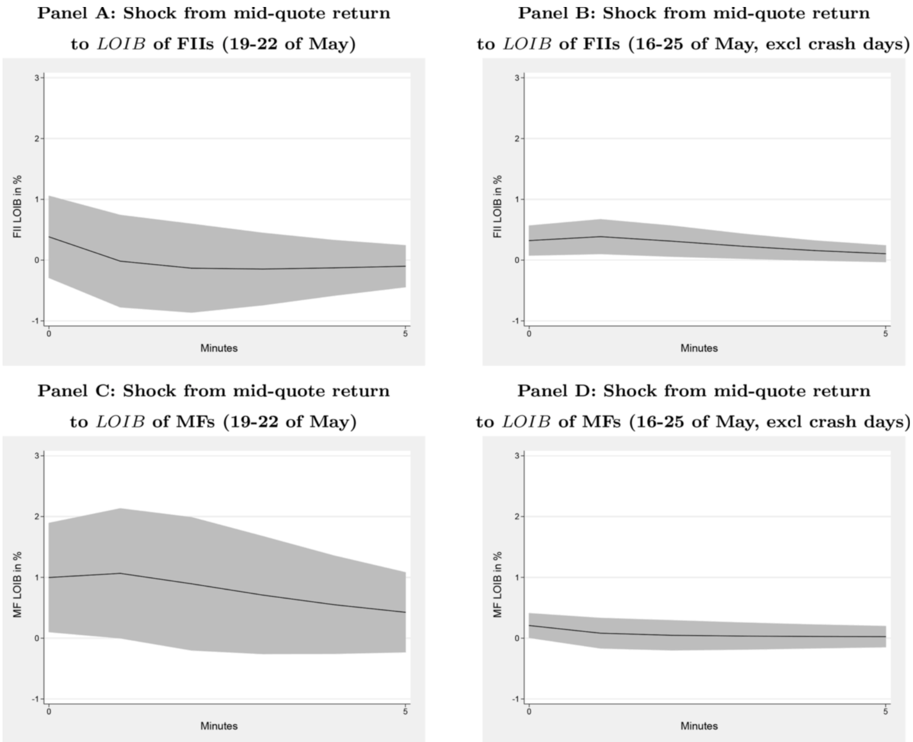


Fig. 7. Orthogonalized impulse response functions for *LOIB* from mid-quote returns. This figure shows orthogonalized impulse response functions for limit order book imbalance (*LOIB*) from mid-quote return based on vector-autoregression for 1-min returns, marketable, and limit order imbalances from different trader categories (see equation (5)). We estimate vector-autoregressions for the crash days and for the four non-crash days. We classify traders into three categories: foreign institutions (FIIs), mutual funds (MF), and other traders (Other). For brevity, we report only those impulse response functions that are relevant for our analysis. Data are provided by the NSE.

natural liquidity providers in the stocks they hold, and Da et al. (2011), who find that the Dimensional Fund Advisors Micro Cap fund added 20.5 bps per quarter to performance through liquidity provision.

5.2. Execution quality of FIIs and MFs

In this subsection, we uncover one potential channel that allows MFs to exert a stabilization force in the market. We first examine whether the MFs and FIIs in our sample are opportunistic buyers and sellers, thus systematically providing liquidity throughout our sample period. For that purpose, we plot MFs' and FIIs' cumulative end-of-day inventory position since the beginning of our sample period and the minimum and maximum trading price observed during the day. Note that overnight short selling was not allowed, and therefore negative inventories should be interpreted as a decrease in the starting inventory position.

Panels A and B of Fig. 8 show that FIIs move with the price, while the MFs are indeed opportunistic traders: they buy when the price goes down and sell when the price goes up.[27] Panels C and D show the end-of-day cumulative inventory position for FIIs and MFs that were active on the crash days, respectively. We observe that these MFs were not active before the crash; they bought during the crash and held their inventory position until the end of our sample period. This behavior suggests that MFs were standby liquidity providers and that it took some time for them to deploy their market-making capital to provide liquidity.

In Fig. 8, we show that MFs systematically act as opportunistic traders. Multiple reasons could give rise to such trading patterns, and in the following analysis, we test one possible explanation. If MFs trade as if they had limit prices for buying and selling based on some notion of "fair value," then it should naturally lead to opportunistic trading through patient buying (selling) at the volume-weighted average price below (above) Other traders' volume-weighted price (i.e., there should be a better quality of trade execution).

To evaluate the quality of trade execution, for each trader l on day k, we compute the volume-weighted average price of its transactions relative to the daily volume-weighted average price of all transactions for the buy and sell side separately. Then, we regress it on dummy variables that equal one if a trader belongs to either FIIs or MFs; on a dummy variable that equals one for traders active on the crash days, the interaction between them, and day fixed effects (FE_k):[28]

[27] Perold and Tierney (1997) document that Numeric Investors behaved in this way when taking positions based on their "fair value" model.
[28] We do not use aggregation for trader categories because within each category there might be traders with different strategies.

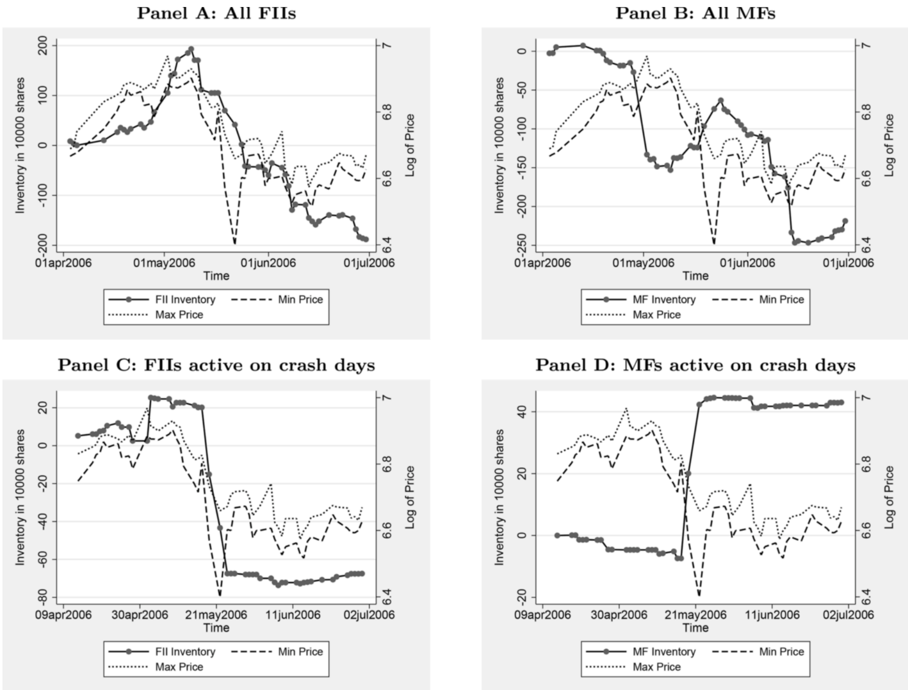


Fig. 8. Cumulative inventories of FII and MF. This figure shows FIIs' and MFs' cumulative end-of-day inventory position in the spot and futures markets. Panel A (Panel B) shows the cumulative end-of-day inventory position of all FIIs (All MFs) in our sample, while Panel C (Panel D) show the cumulative end-of-day inventory position of FIIs (MFs) that were active on the two crash days: May 19 and May 22, 2006. Negative values of cumulative inventories should be interpreted as a decrease in the starting position as of the beginning of April 2006. Data are provided by the NSE.

Table 7

Quality of trade execution. This table shows the regression for the terms of execution FIIs and MFs face as compared to Other traders (see equation (6)) separately for buy and sell volume. As a dependent variable, we use the volume-weighted average price for each trader relative to the volume-weighted average price for all traders during the day. *Active* is a dummy variable that equals one if a trader was active during May 19 and/or May 22, 2006. We use day fixed effects. We cluster standard errors by day and trader. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. *t*-stats are reported in parentheses. Data on trader IDs, orders, and trades for anonymous stock for the period from April to June 2006 are provided by the NSE.

	Buy		Sell	
	(1)	(2)	(3)	(4)
FII	0.11	0.06	−0.34***	−0.31***
	(0.97)	(0.44)	(-3.60)	(-2.77)
MF	−0.26**	−0.22*	−0.12	−0.07
	(-1.98)	(-1.81)	(-1.18)	(-0.71)
FII × *Active*		0.27**		−0.23
		(2.06)		(-0.88)
MF × *Active*		−0.16		−0.34
		(-0.30)		(-1.28)
Active		−0.09***		−0.02
		(-4.67)		(-1.51)
Constant	99.99***	100.01***	100.05***	100.05***
	(726,744.29)	(25,934.47)	(458,248.17)	(40,866.56)
Observations	265,362	265,362	254,224	254,224
Adjusted R^2	0.018	0.019	0.031	0.031
Day FE	Yes	Yes	Yes	Yes
Clustered SE	By Trader and Day	By Trader and Day	By Trader and Day	By Trader and Day

$$\frac{VWAP_{lk}}{VWAP_k} = \sum_k \alpha_k FE_k + \beta_1 FII_{lk} + \beta_2 MF_{lk} + \beta_3 FII_{lk} \times Active_l + \beta_4 MF_{lk} \times Active_l + \beta_5 Active_l + \varepsilon_{lk}. \tag{6}$$

Table 7 shows that, for the specification, including interaction variables, MFs buy a stock at a price relative to the daily VWAP of all transactions that is 0.22% lower than the volume-weighted average price of Other traders, while FIIs active on the crash days buy at a price 0.27% higher than the volume-weighted average price of Other traders. FIIs also sell stock at a price relative to the daily VWAP of all transactions that is 0.31% lower than the volume-weighted average price of Other traders. In other words, MFs are patient buyers, while FIIs are impatient sellers, and this effect is not solely driven by those MFs and FIIs active during the crash days; rather, it is a general characteristic of the traders that belong to these categories during our sample period. MFs move slowly not because they are slow to react to the market signal, but because they wait until the price hits their buying limit estimate from the "fair value" model.

6. Conclusion

Stock price crashes, though infrequent, do occur with adverse consequences. The Flash Crash of May 6, 2010 drew regulators' and exchanges' attention to the need to understand the role of different types of traders during crashes and their recoveries as opposed to normal periods.

Based on a dataset with unique identifiers for each broker-trader combination, along with their legal entity type, we provide a comprehensive analysis of the interactions among mutual funds (MFs), which hold a large inventory of stocks and can tolerate deviations from their desired inventory positions for a longer period of time; foreign institutional investors (FIIs), who trade based on their global perspective; and other traders, who are characterized by shorter trading horizons. We acknowledge the limitation of our data as we only concentrate on one large representative stock in the NSE. However, we believe that given the very granular nature of our data and the fact that we concentrate on one of the largest stocks on the NSE, which was the third-largest stock exchange after the NYSE and NASDAQ as of 2006, our results of liquidity provision during fast intraday crashes can be generally applicable to other major limit order book markets.

Both MFs and FIIs trade much less than other traders; nevertheless, their importance during fast intraday crashes should not be neglected. In line with studies indicating that large sell orders initiate crashes, we find that large sell orders by FIIs exert a downward pressure on the stock price. During the first crash, MFs, though slow to move in, started buying in sufficient quantities to help stop the crash and initiate price recovery. In the second crash, trading was halted. When trading resumed, MFs once again started buying in sufficient quantities to promote the price recovery. We also provide insight on the potential channel that allows MFs to exert a stabilizing force in the market. In particular, we show MFs are patient traders that trade with better execution quality than other traders. We add to the literature by concentrating on micro-level high-frequency analysis of liquidity provision by MFs.

Our findings emphasize the role of well-capitalized standby liquidity providers like MFs, which can deploy capital into the market when the rewards are sufficient, thereby providing much-needed liquidity. This process takes time, since such liquidity providers have to understand the reasons for the crash and may also require a large price concession. Circuit breakers, while providing the needed time for standby liquidity providers to move in, may not provide the necessary incentives. To the extent that there are no alternative mechanisms to provide the necessary incentives for attracting standby liquidity providers, rare crashes may be inevitable in markets where competitive forces result in thinly capitalized intermediaries (such as high-frequency traders) being the de facto liquidity providers.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.finmar.2021.100646.

Appendix B. Data, markets, and liquidity provision findings in a few closely related studies

Table B1 provides the summary of the findings in a few closely related studies with a particular focus on the data used, market under investigations, type of crisis (if any), and the findings in terms of liquidity provision.

Table B1
Data, Markets, and Liquidity Provision Findings in a Few Closely-Related Studies.

Author (year)	Data	Market	Liquidity Provision Findings	Crisis period	Duration of crisis
Panel A: Equities					
Keim (1999)	Case study: DFA's "9–10" fund	Equities	DFA's "9–10" fund provided liquidity for small cap stocks during 1982–1995		
Da et al. (2011)	Quarterly holdings of mutual funds and data from Dimensional Fund Advisors	Equities	DFA's Micro Cap fund earned 20.5 bps per quarter from liquidity provision		
Anand et al. (2013)	Data from Abel Noser Solutions at the transaction level including institution and broker ids, date and time of execution	Equities	There was a subset of institutions that engaged in long-term liquidity supply that was crucial for market recovery from the 2007–2009 financial crisis	2007–2009 financial crisis	Several years

(continued on next page)

Table B1 (*continued*)

Author (year)	Data	Market	Liquidity Provision Findings	Crisis period	Duration of crisis
Cella et al. (2013)	Quarterly holdings of mutual funds	Equities	Mutual funds with short investment horizon demand liquidity during market turmoil therefore amplifying the initial shock	Main focus on the collapse of Lehman Brothers	Several years
Giannetti and Kahraman (2018)	Quarterly holdings of mutual funds and hedge funds	Equities	Open-end funds are less likely to engage in long-term arbitrage due to high risk of fund outflows. Focus on fire sales and shifts in noise trader demand		
Çötelioğlu et al. (2020)	Data from Abel Noser Solutions at the transaction level including institution and broker ids, date and time of execution	Equities	Leverage, age, asset illiquidity, and reputational capital are relevant characteristics that explain the exposure of hedge funds' liquidity supply to funding conditions		
Panel B: E-mini S&P 500 futures					
Easley et al. (2011)	Intraday transactions data	E-mini S&P 500 stock index futures	Flow toxicity increased prior to the Flash Crash making liquidity provision costly which in turn might lead to non-designated liquidity providers withdrawing from the market	Flash Crash of May 6, 2010	Intraday
Kirilenko et al. (2017)	Intraday audit trial transaction-level data with trader ids from CFTC	E-mini S&P 500 stock index futures	Most active non-designated liquidity providers do not change their behavior during the Flash Crash and thus, are not the ones to be blamed for its occurrence and/or exacerbation	Flash Crash of May 6, 2010	Intraday
Menkveld and Yueshen (2019)	Intraday trade and quote data	E-mini S&P 500 stock index futures, SPY, and 50 most crashed stocks	During Flash Crash cross-market arbitrage broke down, making it costly for the large seller trading on one market venue only since she has to rely on local liquidity supply	Flash Crash of May 6, 2010	Intraday
Panel C: Bonds					
Mitchell et al. (2007)	Quarterly fund holdings	Convertible bonds (over-the-counter market)	Convertible bond arbitrage hedge funds which experienced large redemptions were the main liquidity demanders, while multistrategy hedge funds supplied liquidity	2005–2006	Several years
Manconi et al. (2012)	Quarterly fund holdings	Corporate bonds (over-the-counter market)	Funds retained illiquid securitized bonds and sold more liquid corporate bonds contributing to the propagation of crisis from securitized product market to corporate bond market	2007–2009 financial crisis	Several years
Anand et al. (2020)	Monthly inferred flows of mutual funds	Corporate bonds (over-the-counter market)	Subset of funds earn positive alpha from liquidity provision, they are quite persistent in their trading style even during market turmoil and in the presence of large redemptions		
Panel D: Various instruments (hedge funds)					
Aragon (2007)	Monthly hedge fund returns from TASS database	Various financial instruments	Hedge funds with more share restrictions invest in less liquid assets		
Agarwal et al. (2009)	Combination of TASS, CISDM, HFR and MSCI hedge funds databases (analysis is conducted at annual frequency)	Various financial instruments	Hedge funds with longer lock-up periods earn higher returns consistent with the ability of manager to invest in illiquid assets		

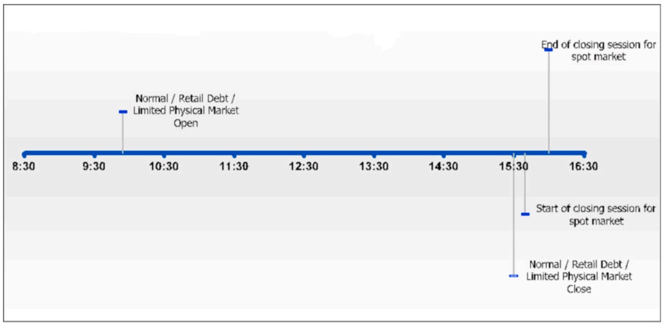
Appendix C. Description of the National Stock Exchange

The National Stock Exchange of India Ltd. (NSE) was incorporated in November 1992, following the liberalization of the Indian financial market and the official establishment of the Securities and Exchange Board of India in 1992. The process of financial liberalization has supported the development of a large group of stock exchanges in India. The NSE and the Bombay Stock Exchange (BSE) are the largest stock exchanges in the country based on market capitalization and traded volume, though there are a total of 21 exchanges that actively operate in India; 97.71% (55.99%) of stocks are traded daily on the NSE (BSE). In 2011, the market capitalization of stocks traded on the NSE was Rs. 67 trillion (USD 1.5 trillion), while the total market capitalization of stocks traded on the BSE was Rs. 68 trillion (USD 1.5 trillion).

The NSE is a fully automated screen-based platform that works through an electronic limit order book in which orders are time-stamped and numbered and then matched on price and time priority. The NSE requires all traders to submit their orders through certified brokers who are solely entitled to trade on the platform. These brokers are trading members with exclusive rights to trade, and they can trade on their own account (proprietary trades) or on behalf of clients. Brokers can trade in equities, derivatives, and debt segments of the market. The number of active trading members has grown from 940 members in 2005 to 1373 members in 2012. Most of them trade in all segments of the market. Every day, more than two million traders actively trade on the platform through several trading terminals located throughout India. While there are no designated market makers on the NSE, a small group of de facto market makers typically control a large portion of trading.

Futures contracts have been trading on the NSE since November 2001. These futures contracts have a three-month trading cycle, with each contract trading for three months until expiration. Every month, a new contract is issued. So, at any point in time for a given underlying stock, there are three futures contracts being traded.

In 2006, trading sessions for both stock and futures markets were between 9:55 a.m. and 15:30 p.m., with a closing session of 20 min from 15:40 p.m. to 16:00 p.m., only for the spot market. Fig. C1 shows the trading day timeline in more detail.



Time	Event
9:55	Nomal / Retail Debt / Limited Physical Market Open
15:30	Nomal / Retail Debt / Limited Physical Market Close
15:40	Start of closing session for spot market
16:00	End of closing session for spot market

Fig. C1. Trading day timeline. This figure shows the trading day timeline of the NSE as of 2006.

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